Maths for ML

Nipun Batra

IIT Gandhinagar

July 30, 2025

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3.

$$\epsilon^{\mathsf{T}}\epsilon = \sum \epsilon_{\mathsf{i}}^2$$

Scalar Property

4. For a scalar s

$$s = s^T$$

Gradient Vector

5.

$$abla_{ heta}\mathbf{s} = egin{bmatrix} rac{\partial \mathbf{s}}{\partial heta_1} \ rac{\partial \mathbf{s}}{\partial heta_2} \ dots \ rac{\partial \mathbf{s}}{\partial heta_N} \end{bmatrix}$$

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$$Z \text{ has a property } Z_{ij} = Z_{ji} \implies Z^{T} = Z$$

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}_{2 \times 1}$$

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$$\theta^T Z \theta = e \theta_1^2 + 2f \theta_1 \theta_2 + g \theta_2^2$$

The term $\theta^T Z \theta$ is a scalar.

Matrix Rank

Since *X* has fewer rows than columns, its maximum rank is equal to the maximum number of linearly independent rows. And because neither row is linearly dependent on the other row, the matrix has 2 linearly independent rows; so its rank is 2.

Matrix Inverse

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$$\begin{bmatrix} 2 & 1 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 0.8 & -0.2 \\ -0.6 & 0.4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
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Not every square matrix has an inverse; but if a matrix does have an inverse, it is unique.